Building Energy Modeling Approaches

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Buildings use up to 40% of the global primary energy and 30% of global greenhouse gas emissions, which may significantly impact climate change. Heating, ventilation, and air-conditioning (HVAC) systems are among the most significant contributors to global primary energy consumption and carbon gas emissions. Extensive research and advanced HVAC modeling/control techniques have emerged to provide better solutions in response to the issues.

advanced HVAC technology | building energy modeling | white-box model | grey-box model | black-box model

1. Introduction

The building sectors (e.g., commercial and residential buildings) account for about 40% of total global primary energy use and about 30% of global greenhouse gas (GHG) emissions [1]. According to the U.S. Energy Information Administration (EIA) [2], the share of the global delivered energy consumption in buildings could be expected to keep increasing from 20% in 2018 to 22% in 2050. Among the energy-related factors in a building, cooling, heating, and the relevant subsystems are the major components of the building energy consumption. In this way, improving a building's heating, ventilation, and air-conditioning (HVAC) and its associated systems has played a crucial role in energy and emission reductions [3]. Because of the complexity of building energy systems' design and operation, various aspects, such as the system's transient energy flow and indoor/outdoor heat interactions, need to be reflected in its design and operation process to increase the overall energy efficiency of HVAC systems [4]. HVAC systems, which provide the cooling and heating supply into a building's thermal zones, can consist of diverse subsystem configurations, including air-loop systems (e.g., heating/cooling coils and supply/return air fans) and water-loop systems (e.g., chillers, boilers, heat exchangers, cooling towers, and water pumps). In addition, the HVAC systems of modern buildings need to satisfactorily deal with various interrelated variables (e.g., temperature, humidity, and velocity) against changeable external disturbances (i.e., outdoor weather conditions) to provide appropriate thermal comfort to occupants [5][6].

In response to this complexity, whole building or system level energy simulations have been widely used to assess appropriate options for energy demand reduction while meeting the indoor thermal comfort requirements and resolving the environmental issues. A good overview of the detailed fundamentals, features of energy-related systems, and main applications for building energy systems and their calculations is given by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) [7][8]. According to the report [8], HVAC systems need to be operated with appropriate control schemes because they are major contributors to the whole building's energy and thermal comfort, keeping the desired environment for occupants inside buildings. There are many considerations during a building energy and heat system analysis, including building age, locations, building envelope materials, energy-related systems, and size. As computational intelligence for building energy system applications is becoming an essential part of the building design and energy management processes [9], the importance of comprehensive energy simulation modeling has been re-emphasized and highlighted. A simulation analysis of heating and cooling systems has become essential at the early design stage and the remedial option stage in the case of new and existing buildings, respectively [10].

The current energy-related modeling techniques, involving the prediction, management, and optimization of the building energy systems design and control, can be grouped into three categories [11], physics-based modeling (i.e., white-box models), data-driven modeling (i.e., black-box models), and hybrid modeling (i.e., grey-box models), by reflecting both physical laws and data-based models. Building energy-related analysis tools and approaches is based on the three methods required to predict thermal and/or energy behaviors and analyze interactions between many connected parts for the building thermal zones and integrated cooling and heating systems. Those modeling approaches can be used to investigate indoor thermal requirements and occupant's needs, which generally depend on the individual performance of energy-relevant sublevel parts (e.g., internal heat gains, HVAC-related systems, and other connected systems). The whole-building energy performance is also integrated by considering the individual components in a building [12]. Since the whole-building energy performance within a building is based on many subsystem components, building energy-related analysis tools can be separated by different options, including building design tools, independent modeling tools of building energy-relevant subsystems, and detailed whole-building energy simulation programs. In addition, many whole-building energy simulation tools and applicable prediction methods exist to determine energy analysis indicators for different design scenarios to minimize energy costs and peak energy consumption [12][13].

To operate HVAC systems more efficiently, the appropriate control and operation of the energy-related systems are key techniques. Since HVAC-related systems of modern buildings consist of many different types of subsystem configurations with a dynamic operation [14], controlling HVAC systems in an effective way between multiple goals (e.g., energy reduction and occupant comfort) is still challenging, specifically in finding the optimal control signals and operating multiple systems simultaneously within a building. The rule-based reactive control strategy is commonly used for traditional HVAC control systems, including pre-determined or tracked schedules [15]. The pre-determined schedules can be used to select proper temperature setpoints based on heuristic rules. The tracked setpoint input schedules can be determined based on the difference between variables (e.g., temperature, pressure, and flow) using techniques such as the proportional, integral, and derivate (PID) control [16]. The rule-based control strategies can also be facilitated to reduce the building energy usage, and thus, GHG emissions, by adjusting the setpoint signals based on an interactive heuristic approach. Although the rule-based feedback control algorithm has been widely adopted for building controls because it is relatively simple and effective for building applications, it is still challenging to have optimal solutions, typically when it must be customized to dynamic response events or seasonal weather conditions [15]. One effective method to resolve such control issues for energy- and environmental-efficient buildings is the model predictive control (MPC) approach [17]. The application of the MPC method for buildings has been actively studied and implemented due to its capability of solving an optimization problem at every decision moment by satisfying conflicting goals, such as energy reduction and indoor thermal comfort. Lately, its application is becoming more powerful because most modern buildings are equipped and connected with complicated heat systems and/or on-site intermittent systems, such as renewables and/or grid connections. In addition, the recent trends in the affordable cost of relevant hardware components (e.g., controllers, communication infrastructure, and sensors) and the ease of application have led to the success of the MPC for building applications [18][19].

Given that MPC applications can effectively predict a building's future behaviors (e.g., thermal demands and/or energy savings), using building modeling tools and/or developed mathematical models are essentially considered. As mentioned earlier, three energy modeling categories can be used for building applications with the MPC framework [20]. According to the problem formulation, the three modeling approaches have different challenges and applicability to the MPC. Many recent studies on MPC have been conducted for intelligent building operations by focusing on energy reduction and/or minimization with simultaneous indoor thermal comfort improvement. For instance, Drgona et al. [21] provide a good overview of advanced building control methods by addressing a unified framework of building MPC technologies for real-world applications. Based on their conclusion, although there still have been challenges in MPC market penetration based on the advanced stage of relevant research fields, large-scale MPC implementation in a marketplace could be expected to take place over the coming years because MPC is the most promising solution and has been actively studied for reductions in building HVAC energy and environmental issues.

2. Building Energy Modeling Approaches

2.1. White-Box Modeling Approaches

The white-box modeling methods (known as the physical-based or engineering methods) use physical principles to solve the calculation of thermal and energy behaviors on the whole-building level or for sublevel systems in buildings [22]. A series of mathematical models are built up step-by-step based on elaborate physical functions or thermodynamics of the mass and energy balances, momentum, and flow balance [23]. The common way of making a white-box model for building energy modeling is as follows: building geometry/envelope, internal heat gains (e.g., lights and occupants), sublevel systems (e.g., HVAC and renewable systems), and control and management parameters. Because of such required parameters that involve the building itself and its environmental information, the modeling is relatively complex and time-consuming to obtain adequate and accurate results corresponding to realistic situations in buildings [24].

Although a wide collection of building energy modeling tools was used throughout the building energy community, most tools were traditionally created for design applications, detailed system simulations, and simple operation managements based on homeostatic short-term feedback mechanisms [25][26]. In the case of white-box modeling approaches, building energy modeling tools typically serve the thermal and HVAC system performance analysis of buildings individually based on the definitive input data of building geometries, HVAC systems, internal heat gains, and weather data [12]. The U.S. Department of Energy (DOE) provides a directory of building-related energy modeling tools, as shown in **Figure 1**, which have been traditionally and recently used to improve HVAC energy efficiency or incorporate renewable energy systems to enable the smart building performance [27].

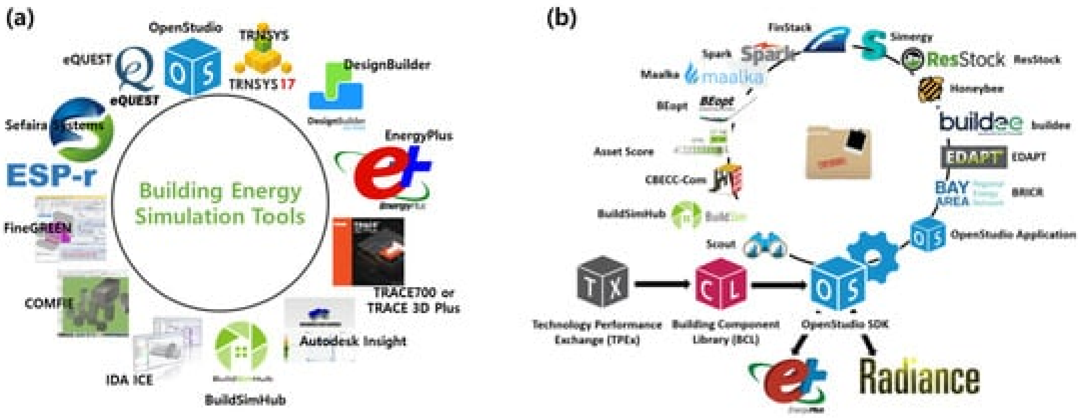

Figure 1. (**a**) Building energy modeling tools found in BEST Directory [28] and (**b**) public and private sector tools and services via the OpenStudio Platform that EnergyPlus directly supports [29].

Hong et al. [12] reviewed the state-of-the-art methodologies on the development and application of computer-aided building modeling tools. In their survey of various building energy modeling tools, only a few simulation tools were available in the public domain even though numerous building design and HVAC system simulation tools were used throughout the building communities. In addition, they mentioned building energy modeling tools that were registered in the International Energy Agency (IEA) Energy Conservation in Buildings and Community Systems (ECBCS) Programme, such as DOE-2, COMIS, and TRNSYS. Their study proved it to be challenging to compare building energy simulation programs in absolute ways because each building simulation tool had its advantages and disadvantages regarding building thermal load and HVAC system levels. **Figure 1**a illustrates the building energy simulation tools available for the building thermal load analysis and HVAC system supports. Additionally, **Figure 1**b shows the public and private sector simulation tools and co-simulation services through the OpenStudio Platform. Based on this platform, a co-simulation analysis can be performed for a more advanced assessment, including to assess system size and real-time optimization, detailed visual comfort analysis, novel HVAC system implementation, etc. [30].

In reference [13], the features of twenty widely used building energy simulation tools were reviewed, including BLAST, BSim, DeST, DOE-2.1, eQUEST, EnergyPlus, ECOTECT, Esp-r, IES, TRNSYS, etc. Crawley et al. [13] also provided detailed trends about building energy modeling tools and compared the features of building simulation tools based on different categories (e.g., general modeling features, zone thermal loads, infiltration, and HVAC systems). Ercan [31] also provided a systematic review of current software tools (e.g., EnergyPlus, TRNSYS, Modelica/Dymola and MATLAB/Simulink) by focusing on the advanced model-based energy evaluation and operation control for building applications associated with HVAC and renewable energy systems.

Those studies [12][13][31] mostly reviewed an extensive list of building energy modeling tools and provided summaries of the current building energy modeling tools, including advantages and disadvantages. This part of these contents will focus on the existing literature, adopting energy modeling tools and techniques to analyze and implement energy-efficient HVAC-related technologies for building applications. **Table 1** lists the representative reviewed research articles regarding white-box models.

Table 1. List of the representative reviewed papers regarding "white-box" models for building energy simulation.

Source	Year	The Focus of Article (Objectives)	Software and Features (White Box-Based Tool)
Coffey et al. [25]	2010	Development of a flexible modeling framework using GenOpt for MPC.	Co-simulation approach with EnergyPlus and TRNSYS.
Beausoleil-Morrison et al. [32]	2012	Development of an integrated system using energy conversion, storage, and distribution technologies for existing whole-building energy simulation tools.	Co-simulation between TRNSYS and ESP-r.
A. L. Pisello et al. [33]	2012	Methodologies to reduce building energy demands through post-occupancy assessment and to optimize building operations.	Modeling and performance evaluation for optimization strategy using EnergyPlus.
Li and Wen [34]	2014	Development of building energy estimation model for online building control and optimization based on a system identification approach.	Online modeling using EnergyPlus and MATLAB.
Dirks et al. [35]	2015	Impact study of climate change on peak and annual building energy use.	Multi-simulation using EnergyPlus.
Davila et al. [36]	2016	Development and validation of an urban building energy model to assess citywide hourly energy demands at building levels.	Modeling and performance evaluation using EnergyPlus.
Oak [37]	2016	Development of the control system using building energy control patterns in response to weather changes.	Co-simulation between BIM and CFD.
Pang et al. [38]	2016	Development of the real-time simulation framework using FMI (functional mockup interface) and FMU (functional mockup units).	Co-simulation with EnergyPlus.
Seo and Lee [39]	2016	Analyzed part load ration (PLR) and operation features with VAV system to evaluate energy savings potential.	Modeling and performance evaluation using EnergyPlus.
Ng and Payne [40]	2016	Evaluated energy savings potential of ventilation-related energy systems	Modeling and performance evaluation using TRNSYS.

Source	Year	The Focus of Article (Objectives)	Software and Features (White Box-Based Tool)
		such as HRV and ERV.	
Chen et al. [41]	2017	Presented the retrofit analysis feature to automatically create and simulate urban building energy models.	Open web-based modeling platform with EnergyPlus.
Kim et al. [42]	2017	Performance evaluation of VRF and RTU-VAV systems under US climate conditions.	Modeling and performance evaluation using EnergyPlus.
Yun and Song [43]	2017	Development of automatic calibration method to reduce the errors between simulated and measured HVAC energy use.	Automated calibration using EnergyPlus.
Alimohammadisagvand et al. [44]	2018	Investigated the effect of demand response (DR) on building energy use and cost.	Modeling and performance evaluation using IDA ICE.
An et al. [45]	2018	Assessed cooling and heating performance of an office building with building-integrated PV windows.	Modeling and performance evaluation using EnergyPlus.
Fernandez et al. [46]	2018	Evaluated energy savings potential of energy-efficient measures in commercial buildings under US climate zones.	Multi-simulation using EnergyPlus.
Wu and Skye [47]	2018	Evaluated energy and cost savings potential of HVAC and renewable systems under US climate conditions.	Modeling and performance evaluation using TRNSYS.
Kim et al. [48]	2018	Investigated the daylighting and thermal effects of a double skin façade system with interior and exterior blind controls.	Modeling and performance evaluation using EnergyPlus and Dysim.
Kim et al. [49]	2018	Presented the detailed procedures for model calibration of a VRF system with a dedicated outdoor air system.	Modeling and calibration using EnergyPlus.
Wu et al. [50]	2018	Investigated commercially available HVAC technologies in terms of energy, comfort, and economic performance for a residential building.	Modeling and performance evaluation using TRNSYS.
Yu et al. [51]	2018	Conducted the comparative analysis to evaluate HVAC energy savings potential of the UFAD system.	Modeling and performance evaluation using EnergyPlus.

Source	Year	The Focus of Article (Objectives)	Software and Features (White Box-Based Tool)
Kim et al. [52]	2019	Presented a methodology of validating fault models that can be used with the building energy simulation tool.	Modeling and calibration using EnergyPlus.
Lee et al. [53]	2019	Investigated the part load ratio and the operating characteristics of a gas boiler to enable energy savings.	Modeling and performance evaluation using EnergyPlus.
Min et al. [54]	2019	Evaluated the energy performance of a multi-split VRF system based on bypass and injection cycles using a numerical simulation.	Modeling and performance evaluation using physics-based mathematical models.
Taddet et al. [55]	2019	Real-time building simulation by implementing a data communication chain in EnergyPlus with hardware-in-loop integration for optimal HVAC operation.	Co-simulation with EnergyPlus.
Guyot et al. [56]	2020	Manual calibration of dynamic heating and cooling systems was conducted using a real office building with 132 zones.	Modeling and calibration using EnergyPlus.
N. Kampelis et al. [57]	2020	Development of a building energy simulation model and calibration based on a trial-and-error approach.	Modeling using EnergyPlus and calibration based on a trial-and-error approach and Kalman filtering.
Cucca and Ianakiev [58]	2020	Development of the co-simulation tool coupling the model of a building energy system with Dymola/Modelica and EnergyPlus.	Co-simulation with EnergyPlus.
Im et al. [59]	2020	Investigated key influential parameters in estimating the uncertainty of energy savings and performed uncertainty quantification for several different scenarios.	Modeling and performance evaluation using EnergyPlus.
Y. Kwak et al. [60]	2020	Proposed a flexible modeling approach to develop a reference building for energy analysis based on parametric analysis.	Modeling and parametric analysis using EnergyPlus.
Seo et al. [61]	2020	Assessment of the cooling energy performance between chiller-based conventional AHU systems and water-cooled VRF-HP.	Co-simulation with EnergyPlus.

Source	Year	The Focus of Article (Objectives)	Software and Features (White Box-Based Tool)
A. Rosato et al. [62]	2020	Development and validation of a dynamic building simulation model for fault detection and diagnostics (FDD).	Modeling and fault detection/diagnostics (FDD) using TRNSYS.
Calixto-Aguirre et al. [63]	2021	Proposed a methodology for the validation of non-airconditioned building thermal simulation to increase building energy efficiency.	Modeling and performance evaluation using EnergyPlus.
Ascione et al. [64]	2021	Development of user-friendly tool for building energy modeling and simulation.	Co-simulation using EnergyPlus and MATLAB.
Bampoulas et al. [65]	2021	Presented an energy quantification framework for various residential building energy systems.	Modeling and performance evaluation using EnergyPlus. [70]
Martinez-Marino et al. [66]	2021	Simulated indoor thermal conditions in a multi-zone building using a co-simulation method.	Co-simulation using TRNSYS [38] and MATLAB.
Piccinini et al. [67]	2021	Development of a novel reduced-order model technology framework [72] for energy savings through cost-effective energy measures.	Modeling and calibration using Modelica ROM.
R. D-Tumeniene et al. [68]	2021	Development of a building energy model for an administrative building and model calibration with measured data.	Modeling and calibration based on an EnergyPlus engine [74] simulation tool.
Neves et al. [69]	2021	Investigated the energy [75][76] and cost impact of geothermal heat pump systems.	Modeling and performance evaluation using EnergyPlus.

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simulation tools (e.g., EnergyPlus, TRNSYS, MATLAB/Simulink, Python, and LabView). The middleware can allow data interaction and exchange between simulation programs and real building automation systems (BASs) that can be developed for existing or novel HVAC systems and their practical applications [39][59]. Modelica is the open standard of an equation-based, object-oriented, and non-proprietary modeling language that has been used in various building applications [77][78]. Since dynamic building energy models for thermal and HVAC component analysis are developed in Modelica, it can be a proper tool for control purposes in future smart buildings [32][77]. TRNSYS is an extensible simulation tool for the whole-building energy simulation, including single- and/or multi-zone buildings [79]. The TRNSYS simulation solves algebraic and differential equations of physics-based energy systems in a whole building. TRNSYS's building energy simulation can provide engineers and researchers with diverse system analyses, from simple systems to advanced HVAC system designs, including HVAC control strategies, renewable energy systems (wind, solar, photovoltaic, hydrogen systems), etc. For pre- and/or post-processing co-simulation, TRNSYS is also able to link with other software tools using a middleware framework (e.g., Microsoft Excel, MATLAB/Simulink, COMIS, etc.) [80]. Esp-r, developed in 1977 by the Energy Systems

Research Unit at the University of Strathclyde, is the European reference building simulation program. Esp-r is capable of modeling thermal zones and simulating the energy flows within combined building HVAC systems with user-specified control actions [81]. In addition, co-simulation between Esp-r and TRNSYS simulation tools or other co-simulation frameworks (e.g., MATLAB/Simulink) allows the strengths of both simulation tools to enable the modeling of innovative buildings and energy system designs [33].

2.2. Grey-Box Modeling Approaches

Grey-box modeling approaches, known as “semi-physical” or “hybrid” modeling methods, combines white- and black-box modeling approaches by considering a hybrid structure with first-principle physics and data-driven strategies [82]. This approach includes the first-principle equations to develop simplified physical processes occurring in the system, and the equations developed from statistical methods and experimental data to improve modeling efficiency with less-understood relationships [83]. The grey-box algorithms include the advantages and shortcomings of the other two methods to represent the system’s actual behavior and efficiently deliver those methods’ benefits [84]. This method can be more computationally efficient than the white-box method and offers flexibility and scalable applications in a model design phase to facilitate the evaluation of energy-efficient means at single or multiple building system levels [85]. This method has been widely used for evaluating energy optimization scenarios when considering building HVAC control or smart-connected system applications [24].

A resistance-capacitance (RC) or thermal network model is commonly used to create grey-box models. Although there are several challenges, such as theoretical limitations and confusing model structures, this approach has been used for many research topics in building energy-related and/or HVAC systems because of the benefits, including: (1) a faster calculation with simplified physics-based models and (2) online controls [24]. The thermal conditions of a building can be expressed with an electric circuit analogy with multiple parameters (i.e., the number of thermal resistances and capacitances) of the model obtained from the measured data, considering available physical insights [86].

The grey-box models can be created based on two subcategories: (1) the physical approach and (2) the semi-physical approach [87]. The major difference between the physical and semi-physical approaches is model structures. For the physical approach, the model structure can be built based on physical models, and the parameters used for the physical models are typically estimated from the measured data. Zhang et al. [88] provided an excellent example of the physical approach for grey-box modeling. Zhang’s study proposed a dynamic, simplified RC-network model for a building ventilation system and obtained the parameter identification effectiveness using experimental data. The semi-physical approaches use physical insights to guide the data through data-driven models. Hossain et al. [89] presented a grey-box modeling approach that uses the Bayesian neural network method to estimate the parameters of a grey-box thermal model with a training dataset. Numerous hybrid model structures of grey-box modeling have been used in the literature. The common grey-box model comprises one first-principle physical submodel and one black-box based submodel with parallel and serial arrangements, even though the number and type of submodels can vary according to application features [90].

The energy modeling of buildings' HVAC and their subsystems or community levels has multiple roles, such as thermal behavior estimation, HVAC size design and optimization, and subsystem/urban energy controls, including real-time operation [91]. For the grey-box modeling approaches, there are numerous representations of research articles regarding RC modeling for building envelopes, single- or multi-zone modeling with internal/exchanged heat gains (e.g., zone air mixed, electrical heat gains, and infiltration), and simplified building HVAC models or district/urban energy prediction models. Among the existing research articles, the topics of thermal load calculation, HVAC operation control/operation, and optimization based on MPC frameworks are relatively dominant for buildings' HVAC and their connected applications [24]. **Table 2** summarizes the list of the more representative papers reviewed, focusing on the grey-box models for the building thermal load and HVAC energy simulation. Because parameter identification is a significant process for grey-box model development, this table also presents how they obtained and/or assumed the parameter identification data for each study. Those parameter values are generally identified based on measured data and/or simulation assumptions.

Table 2. List of the representative reviewed papers regarding "grey-box" models for building thermal load and HVAC energy simulation.

Source	Year	The Focus of Article (Objectives)	Parameter Identification (or Other Features)
Nielsen and Madsen [92]	2006	Evaluated the heat consumption of a large district heating system using a grey-box modeling approach.	Experimental identification with measured heat consumption and climate data.
Kampf and Robinson [93]	2007	Development of a grey-box model to simulate heat flows for a building with an arbitrary number of zones.	Assumed identification and ESP-r were used for model verification.
Balan et al. [94]	2011	To simulate the thermal behavior of a building for energy reduction using a simplified thermal-network grey-box model.	Experimental identification of the model's parameters.
Berthou et al. [95]	2014	Development and validation of a grey-box model by adopting a second-order model to predict thermal behavior in an office building.	Experimental data for the identification process and sensitivity analysis to identify the most important parameters.
Reynders et al. [96]	2014	Development of a robust grey-box model that results in an accurate prediction and long-term simulation in a residential building.	Experimental identification for reliable characterization of the physical properties.
Unerwood [97]	2014	Development of an improved method for the simplified modeling of the thermal response of building components using a 5-parameter second-order grey-box model.	The extraction of the simplified model parameters based on a multi-objective function algorithm.

Source	Year	The Focus of Article (Objectives)	Parameter Identification (or Other Features)
Ogunsola and Song [98]	2015	A simplified RC thermal model using an analytical solution method for an office building.	Experimental data for the identification process and the developed RC model was compared with measured data and a white-box model.
Teres-Zubiaga et al. [99]	2015	Evaluated the thermal performance of a residential building with a grey-box model.	Experimental data for the identification process and improving accuracy.
Jara et al. [100]	2016	Presented the self-adjusting RC-network model for the parameter identification of a simplified lumped parameter model.	First-order method with two resistances, one capacitance, and simulated data used for the identification process.
Ji et al. [101]	2016	Development of the RC-network model with a submetering system for cooling load calculation in a commercial building.	For the identification process, measured data from real buildings and simulated data from an EnergyPlus model were used.
Zhang et al. [88]	2016	Proposed a dynamic, simplified RC-network model for radiant ceiling cooling system integrated with an underfloor ventilation system.	The parameter identification effectiveness determined by experimental data.
Hu and Wang [102]	2017	Development of a self-learning grey-box thermal model to investigate demand response for a HVAC system.	Pre-estimated and scaled parameters for the identification process using measured data.
Li et al. [103]	2017	Simplified RC-network model development and validation for the pipe-embedded concrete radiant floor system.	RC model with two resistances and one capacitance (2R1C), and validation through numerical simulation and experimental data.
Afram et al. [104]	2018	Development of a grey-box model for a residential HVAC system with heat recovery ventilator and air-source heat pump.	Experimental data for the identification process and the developed model was compared with measured data for validation.
Gori and Elwell [105]	2018	Development of a method for the quantification of systematic errors on the thermophysical properties of buildings using a dynamic grey-box model.	Experimental data for the identification process and the comparison against the static method.
Macarulla et al. [106]	2018	Assessment of the potential of using the stochastic grey-box modeling approach to estimate the ventilation air change rate.	Tracer-gas mass balance and experimental data used for the identification process.
P. Bahramnia et al. [107]	2019	Development of a RC-network model and implementation of a model predictive	Experimental data for the identification process and the developed model was

Source	Year	The Focus of Article (Objectives)	Parameter Identification (or Other Features)
		control strategy to optimize both temperature and humidity operations.	compared with measured data by minimizing the optimization index.
Shamsi et al. [108]	2020	An uncertainty framework for reduced-order grey-box energy models in heat demand predictions of the building stock.	The identification process of using an integrated uncertainty approach using a copula-based theory and nested fuzzy Monte Carlo approach.
Thilker et al. [109]	2021	Development of a nonlinear grey-box model for the heat dynamics of a school building with a water-based heating system.	Experimental data with a DAQ system based on IoT sensors for the identification process.
F. Belic et al. [110]	2021	Demonstration of a simple implementation of a RC-network method for multi-zone buildings to save HVAC energy use.	The parameter identification effectiveness determined by simulation and experimental data obtained from the literature.
Joe [111]	2022	Application of MPC with a grey-box model to investigate the operational cost-savings potential of an underfloor air distribution system.	Experimental data used for the identification process and simulation-based case study to quantify the savings potential of the MPC.

, the data [112] en, those ields with [113] ata-driven modeling [114][115] black-box viors in a nsisting of many subsystem configurations, is advancing the use of black-box modeling approaches and simulations. Black-box models for building thermal and energy prediction are generally developed based on historically measured or generated data to capture the hidden mathematical relationships between input and specified output variables using machine learning and statistical methods [116][117]. **Figure 2** represents a general process of machine learning-based black-box modeling approaches. Black-box model approaches have been well adaptable for building HVAC-related applications without the need for detailed physical information about a building. Most projects for building HVAC applications focus on analyzing time-series datasets with training, validation, and testing steps [118].

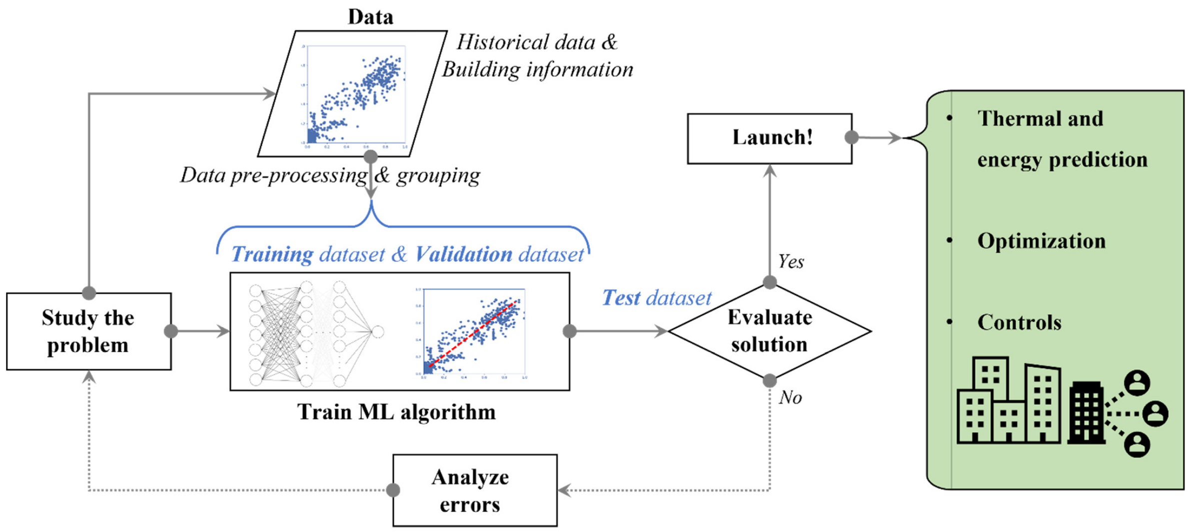

Figure 2. Schematic of a typical machine learning-based “black-box” model approach [119].

The black-box modeling process involves several steps, including data collection, pre-processing, training, validation, and testing datasets to evaluate the implemented machine learning algorithms. For building HVAC system applications, various time-series data variables (e.g., data type, weather conditions, internal heat gain rates, schedules, and operation features of HVAC systems) could be included. A building's physical parameters (e.g., locations, the number of floors, window to wall ratios, and surface construction features) are also important for a cluster analysis based on data collection and pre-processing phases [117]. The black-box model is developed and run on the training dataset in the training process. The results are then compared to the original training data to adjust the different parameters of the algorithm to fit the training dataset [120]. The validation process is considered to tune key modeling parameters to improve the fitting accuracy of the implemented algorithm, which already fits the training dataset, using different datasets [118][121]. The testing process is conducted to evaluate the modeling and predicting performances by running the developed algorithm on the test dataset (e.g., the remaining part of the entire dataset) [118]. After the evaluation, any errors or uncertainty factors could be analyzed to capture practical issues with the model's development (e.g., model input/output parameters and structures), as shown in **Figure 2**.

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